DATA FUSION WITHIN A CONSTRAINED COMMUNICATION ENVIRONMENT

February 1998

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ABSTRACT

In this paper we present some recent results involving track level fusion in a distributed tracking environment. Successful fusion for the application requires that target state estimates and their error covariance matrices be available for processing. For this study, we are dealing with the limitations associated with several of the existing communication links (missing covariance) and how we can recover track covariance matrices from track quality parameters. An algorithm for reconstructing an error covariance from on offboard track system is presented using the notion of an ambiguous measurement set. The performance of this approach is demonstrated in several simulated test cases.

1.0 INTRODUCTION

In a distributed fusion environment where target track level information is communicated from a remote site to a central fusion node, it is important to pass over the target state estimate as well as its uncertainty, as reflected by the covariance matrix. This is because the track level fusion algorithms require both state estimates and covariance to optimally fuse the data at the central node. Unfortunately, within some of the present communication links (JTIDS, Link 11, etc.), it is not possible to send the elements of the covariance matrix. At best, an indicator of state estimator uncertainty is track quality, an integer that can be mapped into an equivalent circular error probability (CEP). In effect, we obtain a circular error uncertainty that contains the same uncertainty as the true covariance error ellipse, but with the resultant loss of the ellipse orientation and eccentricity.

In these conditions, the data fusion algorithm at the central node will be operating on circular error uncertainties from the remote sites instead of the true elliptical uncertainties (covariance). This is suboptimal and can lead to inaccurate fusion results, which in turn, gives a false impression of error performance at the central node. To circumvent these problems we have developed a front-end processing algorithm at the fusion node to back out the parameters of the error ellipse (and hence covariance) from the track quality integers that are sent over the communication channel. Using the concept of a multi-state measurement and a simple correlation metric, it will be shown that, over time, we can quickly determine the correct covariance from the remote state estimate and its quality. This will be demonstrated on a number of simulated scenarios.

REPORT DOCUMENTATION PAGE	Form Approved OMB No. 0704-0188

1. REPORT DATE (DD-MM-YYYY)	2. REPORT TYPE	3. DATES COVERED (FROM - TO)
01-02-1998	Conference Proceedings	xx-xx-1998 to xx-xx-1998

4. TITLE AND SUBTITLE Data Fusion Within a Constrained Communication Environment Unclassified	5a. CONTRACT NUMBER 5b. GRANT NUMBER 5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S) Lobbia, Robert N. ; Owen, Mark ;	5d. PROJECT NUMBER 5e. TASK NUMBER 5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME AND ADDRESS Boeing Information, Space & Defense Systems Seattle, WA98124	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME AND ADDRESS Director, CECOM RDEC Night Vision and Electronic Sensors Directorate, Security Team 10221 Burbeck Road Ft. Belvoir, VA22060-5806	10. SPONSOR/MONITOR'S ACRONYM(S) 11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
APUBLIC RELEASE
,

13. SUPPLEMENTARY NOTES
See Also ADM201041, 1998 IRIS Proceedings on CD-ROM.

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15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19. NAME OF RESPONSIBLE PERSON
			Public Release	9	Fenster, Lynn lfenster@dtic.mil
a. REPORT Unclassified	b. ABSTRACT Unclassified	c. THIS PAGE Unclassified			19b. TELEPHONE NUMBER International Area Code Area Code Telephone Number 703767-9007 DSN 427-9007

The format of this paper will be as follows. In section 2, we present a mathematical formulation of the problem. A brief description of using a multi-state (ambiguous) measurement with a chi-square correlation metric is proposed to back out the ellipse parameters. To validate performance of this design, section 3 will demonstrate algorithm execution in several simulated test scenarios. The resulting analyses will be performed in a Monte-Carlo mode to insure the results are repeatable over different process and measurement noise sequences. Finally, in section 4, we summarize our results and state the key conclusions forthcoming from this study.

2.0 MATHEMATICAL FORMULATION

In this section, we start by introducing the fusion equation for track level processing. When offboard/remote position state estimates are passed over to the fusion node, we show how the position covariance elements can be equivalently mapped into error ellipse parameters. When the correct parameters are not available, we will see why fusion error performance can be misleading. Then some early attempts at backing out the true covariance are discussed. The new design is then described, and it is shown how we convert lack of input covariance data into measurement level ambiguity, where application of correlation metrics over time will help to sort out the input ambiguities.

2.1 THE FUSION PROCESS

The algorithm for fusing offboard/remote track level information is defined by:

$$\begin{aligned}\hat{x}_F(k+1/k+1) = P_F(k+1/k+1)\big[&P_F^{-1}(k+1/k)\hat{x}_F(k+1/k) + \\ &P_o^{-1}(k+1/k+1)\hat{x}_o(k+1/k+1) - P_o^{-1}(k+1/k)\hat{x}_o(k+1/k)\big]\end{aligned} \tag{1}$$

$$P_F^{-1}(k+1/k+1) = P_F^{-1}(k+1/k) + P_o^{-1}(k+1/k+1) - P_o^{-1}(k+1/k) \tag{2}$$

where $\hat{x}_F(\cdot)$, $P_F(\cdot)$ represent the fusion node state estimate and covariance
$\hat{x}_F(\cdot)$, $P_o(\cdot)$ represent the offboard state estimate and covariance

and the discrete time argument k+1/k represents a prediction to time k+1 based on data to time k, and k+1/k+1 represents an update to the prediction based on new data at time k+1.

This is the standard inverse form of the Kalman filter since we are propagating the inverse of the covariance (information). See Ref. 2 for more detail. For ease of presentation in this paper, we assume that the state vector dimension is two (x and y Cartesian coordinates) and the resulting covariance is 2x2. Extension to the offboard 3-dimensional position (x, y, z) estimates and fusion state vectors with six-dimensional position/velocity components is straightforward.

Now, when the offboard estimator is not able to send over the covariance, $P_O(\cdot)$, to the fusion node, and instead passes over a quality, the best we could do is to map this into a CEP, which in geometric space is a circle of radius, r, that represents the 50% probability area within which the true target should lie. This circular error distribution, or for that matter, any elliptical error distribution, can be mapped back into the entries of the 2x2 covariance matrix via the standard transformations:

$$P = \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} \text{, the 2x2 covariance} \tag{3}$$

where
$$P_{11} = \frac{a^2 + b^2}{2} + (\cos^2\theta - \sin^2\theta)\left(\frac{a^2 - b^2}{2}\right) \tag{4}$$

$$P_{22} = \frac{a^2 + b^2}{2} - (\cos^2\theta - \sin^2\theta)\left(\frac{a^2 - b^2}{2}\right) \tag{5}$$

$$P_{12} = \left(\frac{a^2 - b^2}{2}\right)\sin 2\theta \tag{6}$$

and
a = semi-major axis of the one sigma error ellipse
b = semi axis of the one sigma error ellipse
θ = ellipse inclination from true north (y axis)

It is easy to see that for a circular error distribution, the resulting covariance will be diagonal with equal entries along the diagonal. It is also apparent from this discussion that by specifying a quality (and hence CEP), we have one parameter that defines the circular radius, and equivalently, the covariance diagonal entry. Clearly, we have lost information embedded in a more general elliptical area which is defined by three parameters (a, b, θ). The quality is derived by creating a circular area to match the elliptical area. In effect, we have:

$$\pi r^2 = \pi\, a \cdot b \tag{7}$$

or
$$r = \sqrt{a \cdot b} \tag{8}$$

Where in (7), we have assumed the radius for the 50% CEP area has been scaled down to 39.4% probability (one sigma, 2-dimensional). If this circular error distribution is now used at the fusion node, we expect suboptimal performance in both data correlation and fusion update performance. More significantly, the fusion update will produce a covariance based on an incorrect interpretation of the offboard covariance. It should be clear that the error performance can become seriously degraded when the offboard covariance (and hence error ellipse) exhibits a high value of elliptical eccentricity $(\sqrt{a^2 - b^2}/a)$.

The question now becomes, given r, can we back out the ellipse parameters, {a, b, θ}, and use these via Eq. (4) through Eq. (6) to construct an offboard covariance matrix, $P(\cdot)$? This is an effective mapping from one parameter, r, to three parameters {a, b, θ} or {P_{11}, P_{22}, P_{12}}.

A number of studies have been conducted over the last several years to accomplish this. Some of the more interesting studies were conducted at Mitre Research facilities in Bedford, MA (Ref. 1). The research there looked at a variety of techniques for backing out covariance in JTIDS and Link 11 communication channels. The one technique that looked the most promising was to use time averaging of the offboard state estimates from a given target to compute the predicted covariance of the target. Unfortunately, the derivation for the algorithms was based on assumptions that were not always satisfied. So, although the results may look good for one scenario, there was no guarantee it would work well in other scenarios.

2.2 DESIGN APPROACH

In our problem formulation for the Rome Laboratory study, we were faced with a very similar problem as the work performed at Mitre. To operate in the OBATS (offboard augmented theater surveillance) environment, we needed to perform fusion at the track level on a number of distributed airborne platforms. The communication channel under consideration was JTIDS, so the same problem issue arose in terms of extracting covariance data from a track quality parameter. However, our design philosophy for backing out the covariance was different than the previous work that had been done. Our approach was based on creating an ambiguous set of potential covariance matrices that all mapped into the same equivalent CEP area. Then at each time sample, each potential covariance matrix along with the offboard state estimate were passed into a normalized chi-square statistic of the form:

$$(\hat{x}_o - \hat{x}_F)^T (P_{oi} + P_F)^{-1} (\hat{x}_o - \hat{x}_F) = \gamma^2 \tag{9}$$

where $\hat{x}_F, P_F$ represent the fusion node state estimate and covariance

$\hat{x}_o =$ offboard state estimate

$P_{oi} =$ one realization of an offboard covariance from the created ambiguous set

The time arguments have been left off for simplicity.

The idea is to monitor this statistic over time for each covariance realization, P_{oi}. When the correct covariance is inserted into this metric, we expect a lower chi-square score than when an incorrect covariance is used. Thus the notion of an ambiguous measurement was created, an offboard state estimate, $\hat{x}_o$, along with a set of potential covariances, P_{oi}. These were all run in parallel through the chi-square association logic at the fusion node in order to not only gate in any potential offboard estimates, but also to select the appropriate covariance to use. This is illustrated in Fig. 1 below.

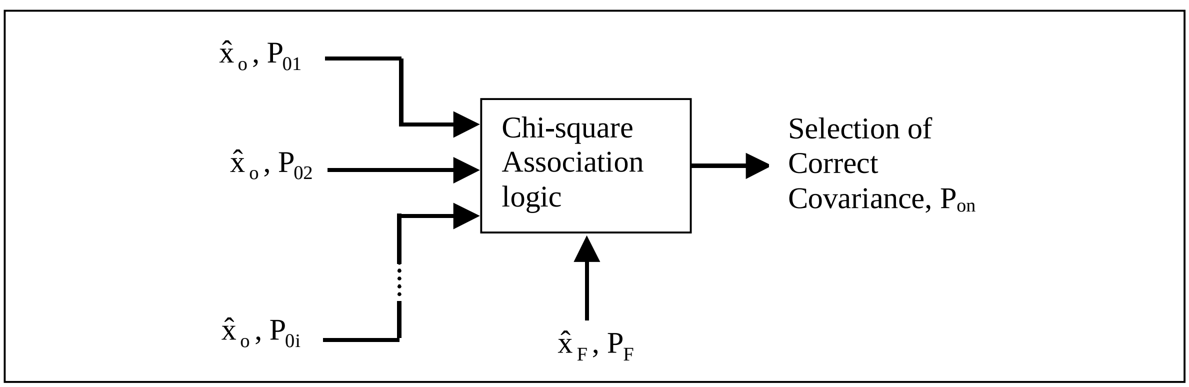

Figure 1. Chi-square Test for Covariance Selection

The next issue becomes, how fine do we discretize the potential set of ambiguous covariances so that we can capture the true covariance in one of the realizations? For our studies, we chose to use a set of 21 potential covariances. These were defined in terms of 21 potential error ellipses: one circular ellipse and 20 true ellipses (a/b = 5, 10, 15, 20, 25, θ = 0 degrees, 45 degrees, 90 degrees, 135 degrees).

In the next section we will present the results of running several test scenarios involving multiple fusion platforms tracking against a constant velocity target.

3.0 TEST RESULTS

To assess performance of the algorithm design, we constructed a set of five simulated test scenarios involving two airborne fusion platforms (at 300 knots speed) and one constant velocity target (at 600 knots). Each of these scenarios differed with respect to geometric placement of the units and their respective headings.

Figures 2 through 4 present the trajectories for three of these scenarios. P_{o1} and P_{o2} represent the fusion platform and offboard platform, respectively. T_{o1} represents the target trajectory. Tracking was performed on range/azimuth radar measurements with errors commensurate with airborne radars.

Now to compute the performance of our covariance selection algorithm we ran Monte-Carlo analyses (50 runs) on these test scenarios. We monitored the value of the chi-square metric in eq. (9) as a measure of how well each covariance selection was performing (low value being good).

Figures 5 through 7 present the results of this Monte-Carlo analysis for three test scenarios described above. In each of these figures, we have overlaid the effects of using different ellipse orientations, θ, for a given ratio of a/b. The true a/b in all scenarios was 23. Because of discretization procedure, we found the best performance using a/b = 25, and this was as expected. For ellipse orientation, we found that the true orientation would change over time, e.g., for scenario 1, starting at 45 deg and ending at 0 deg. Looking at all three of the scenarios, we found that the ellipse orientation having the lowest chi-square value closely matched the true ellipse orientation over time. This was a very encouraging result as we can now use the chi-square metric as an aid in selecting the correct ellipse ratio, a/b, and orientation, θ.

The basic idea is to monitor the statistic in eq. (9) in real time, and to use it as a basis for selecting the covariance which yields a minimum value. Since this could lead to ellipse parameters which jump around from one time scan to the next, it is suggested that the output of eq. (9) be passed through a low pass filter to provide a smoothed output for each potential covariance, P_{oi}. The smoothed outputs can then be used to select the covariance that best matches the true offboard covariance.

We have presented three of the five scenarios here to conserve space. However, the other two scenarios performed equally as well as the first three.

To implement the above selection procedure in a real-time application, we would propose that the chi-square testing for each covariance in the ambiguous set be dedicated to parallel CPUs. For faster machines, the set of 21 covariances (in our studies) can be fed sequentially through the chi-square metric and a comparison executed after all 21 scores are generated. For our application, we were able to run faster than real time using the latter method on a Sun SPARC platform.

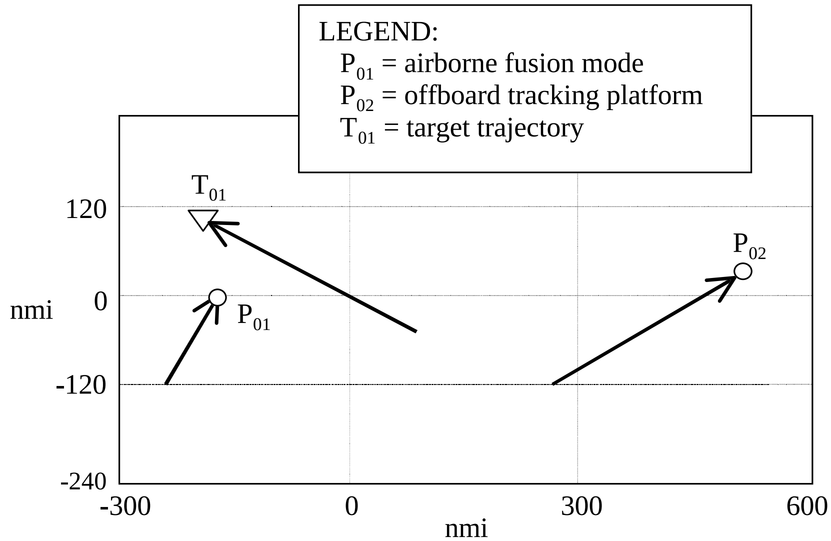

Figure 2. Scenario 1, Platform / Target Geometry

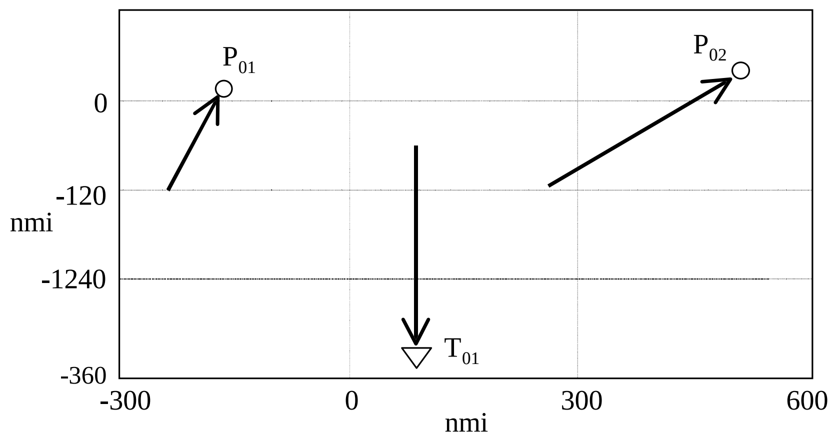

Figure 3. Scenario 2, Platform / Target Geometry

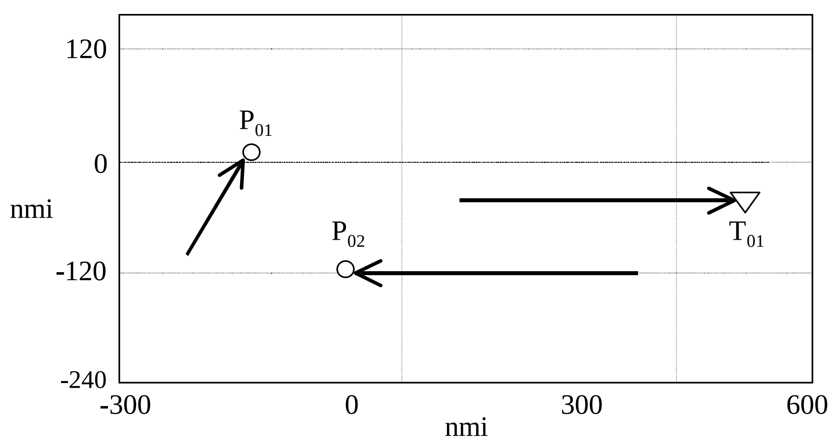

Figure 4. Scenario 3, Platform / Target Geometry

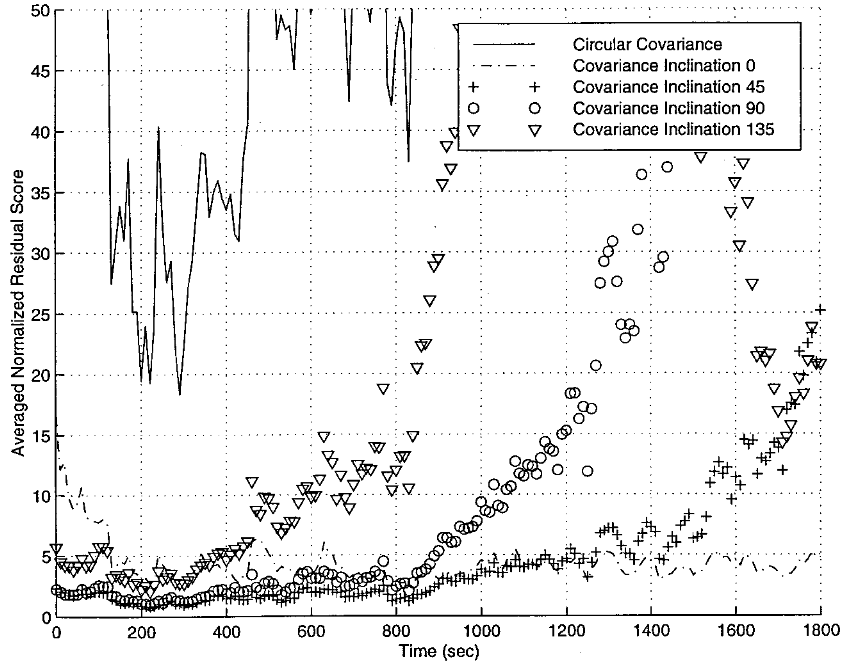

Figure 5. Scenario 1, 50 Monte-Carlo Runs, Semi Major Axis is 25 Times the Semi Minor Axis, Track Quality 7

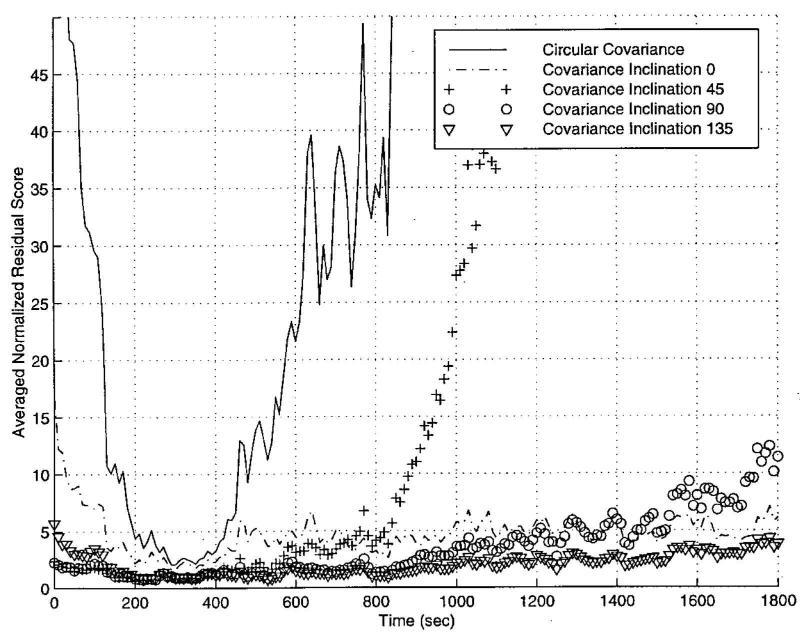

Figure 6. Scenario 2, 50 Monte-Carlo Runs, Semi Major Axis is 25 Times the Semi Minor Axis, Track Quality 7

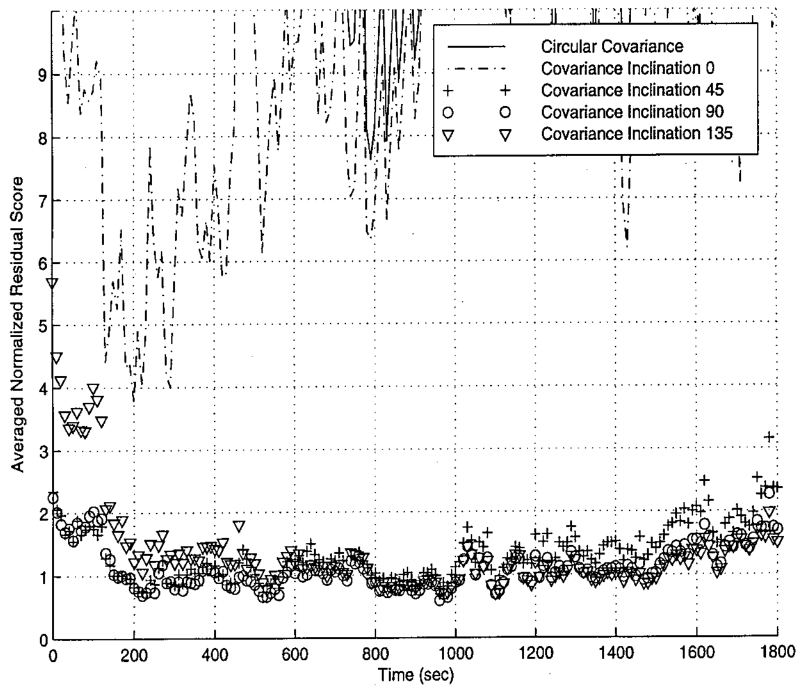

Figure 7. Scenario 3, 50 Monte-Carlo Runs, Semi Major Axis is 25 Times the Semi Minor Axis, Track Quality 7

4.0 SUMMARY AND CONCLUSION

For this study we have developed a practical approach for backing out the covariance matrix from track quality parameters sent over a constrained communication channel like JTIDS. This is particularly important in track level fusion applications involving distributed processing sites. A computation of the true offboard covariance is required if we are to perform a successful correlation and fusion of the offboard data – track qualities/CEPs by themselves will lead to erroneous results.

Our simulated results have indicated, via Monte-Carlo analysis, that the algorithm is successful in picking out the ellipse parameters (and hence covariance). This is encouraging because the algorithm can be configured to operate in a real-time environment. Additional studies are warranted to look at the effects of tracking in a multi-target environment to determine when dense target scenarios could create problems with associating the correct target between pairs of distributed tracking platforms.

REFERENCES

[1] K.H. Kim, “Development of Track-to-Track Fusion Algorithms,” Proceedings of the American Control Conference, Baltimore, MD, June 1994.

[2] R. Lobbia, M. Kent, “Data Fusion of Decentralized Local Tracker Outputs,” IEEE Transactions on Aerospace and Electronic Systems, Vol. 30, No. 3, July 1994.

ACKNOWLEDGMENTS

This work was supported by the OCSM directorate of Rome Laboratory under Air Force contract number F30602-96-C-0162. We wish to acknowledge Eric Jones and Jon Jones from Rome Laboratory, and Martin Liggins from SAIC for their support and guidance and for the opportunity to work on several of the challenging problems connected with the OBATS program.